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Research Article

Optimized Fault Diagnosis Algorithm under GAN and CNN Hybrid Model

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The network fault diagnosis algorithm is one of the most important algorithms to solve network transmission problems. In traditional network fault diagnosis, it mainly analyzes and troubleshoots the fault manually by comparing the alarm information of the network performance index with the expert experience database. Diagnosis methods based on manpower analysis will take up much material resources and manpower and increase maintenance costs. Therefore, there is an urgent need for a more efficient and intelligent fault diagnosis technology. In addition, as the current network is becoming more and more complex, and based on this consideration, a semi-supervised fault diagnosis algorithm is studied in this paper. It is a combination of the GAN and CNN models. Meanwhile, the method of combining relief and mutual information is applied to reducing the dimensionality of network feature parameters, and the optimal feature combination is selected. The fluctuations in the convergence of the generated confrontation network model are stabilized. Moreover, the simulation software is used to build the heterogeneous wireless network scenario studied. Meanwhile, an improved fault diagnosis model is constructed to verify that in the case of both GAN and CNN models, the accuracy of fault diagnosis algorithm can reach 98.6%, which is significantly higher than other comparative analysis methods. It has contributed to ensuring the user's service experience and reducing the cost of network maintenance and operation.

1. Introduction

Nowadays, with the continuous deepening of research on key technologies such as massive MIMO technology, full-duplex technology, and network slicing, the 5th generation (5th Generation Mobile Communication Technology, 5G) mobile communication is gradually shifting from being technology-centric to being user-centric [1]. Its higher transmission rate satisfies the transmission of big data such as high-definition video and VR/AR virtual reality. Besides, its lower network delay and higher reliability satisfy real-time applications such as autonomous driving and telemedicine [2]. At the same time, its larger system capacity and low power consumption also provide conditions for the access of hundreds of billions of devices, and the Internet has gradually expanded to the Internet of Things (IoT) [3]. In addition, from the initial communication between people to the communication between people and things, and even the communication between machines and machines, the real interconnection of everything is realized [4]. Moreover, different applications such as VR/AR, smart grid, vehicle networking, and autonomous driving also have different requirements for network functions [5]. To meet the needs of different types of services under the constraints of limited spectrum resources, the future development trend of wireless networks is bound to be a heterogeneous network integrating multiple wireless access technologies such as WLAN, LTE, and 5G [6].

The ultra-dense heterogeneous network technology composed of micro base stations and macro base stations. It has also been proposed to increase the capacity of the network system to cope with the exponentially increasing mobile data traffic [7]. Among them, fault management is one of the core problems [8]. In a heterogeneous network environment, the occurrence and propagation of faults are inevitable, and it can ensure network stability and service reliability to timely and accurately detect and diagnose network faults [9]. Nowadays, academia is conducting in-depth research and discussion on fault diagnosis technology in heterogeneous networks, and many efficient network fault diagnosis schemes have been proposed.

The dynamic and adaptive network fault diagnosis method studied in this paper can realize accurate detection and diagnosis of network faults in a complex network environment [10], which effectively alleviates the service interruption and network paralysis.

The main innovations of this paper are as follows:

(1) A semi-supervised fault diagnosis model is proposed in order to solve the problem that the complexity of the discriminator network of the traditional model is too high

(2) The strategy of network tracking and monitoring is formulated. The corresponding network data is collected according to the operation system, and then the program of screening the optimal feature combination is compiled to realize the generation of network data and the diagnosis of the network faults

(3) The algorithm of combining GAN and CNN is adopted, and the CNN model is trained by composite data to complete the diagnosis of network faults

The structure of this paper is as follows: Section 1 briefly described the research background, research status and main research work. Section 2 described the relevant working principles of this paper. Section 3 established the relevant research models. Section 4 realized the function modules and algorithm design. Section 5 carried out the simulation experiments to analyze the performance of the proposed method. Section 6 summarizes the three research works of this paper and looks forward to future research work.

2. Related Work

The improvement of computer computing power has also promoted the development of the field of deep learning, thus realizing the rapid mining of useful information in massive data [11]. This section mainly introduces the existing network fault diagnosis technology and the deep learning algorithm used in this paper [12].

2.1. Network Fault Diagnosis Technology. Mobile data traffic is showing a trend of rapid growth. Insufficient network capacity and high requirements for new business service quality need to be solved in future networks [13]. A new type of heterogeneous network is one of the solutions [14]. However, in the complex and changeable heterogeneous network environment, how to effectively maintain and manage the network and ensure the normal operation of the network has become the primary problem for operators [15]. Meanwhile, fault diagnosis is the core content of network management. Since the occurrence of faults is inevitable and spreading, their rapid detection and diagnosis are particularly important to the robustness and reliability of the net [16]. In a big and complex communication network, the intelligence and automation of fault diagnosis have also attracted more attention and research [17]. The process of fault diagnosis can generally be divided into three steps:

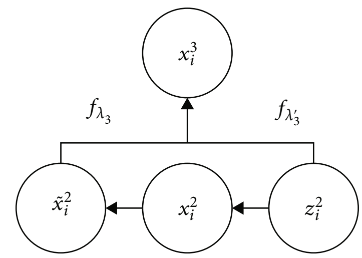

Figure 1: The M-P neuron model.

(1) Fault detection: It refers to the process of judging whether there is a fault- based on the observed network symptoms

(2) Fault location: It refers to the process of inferring the location of the fault based on the collected network parameters

(3) Test: According to the located fault category, analyze the cause of the fault, and then perform a recovery test

2.2. Deep Learning. Deep learning model is actually a neural network with more hidden layers [18], usually more than eight or nine hidden layers. The simplest M-P neuron model is shown in Figure 1.

The neuron multiplies the received input signal by the corresponding connection weight [19], which will be compared with the neuron's bias and output after processing. The output is as follows:

$$y = f\left(\sum_{\infty}^{i=1} w_i x_i - \theta\right). \tag{1}$$

Among them, x_i is the input from the ith neuron, w_i refers to the connection weight of the i-th neuron, and θ is the current neuron bias. $f(\cdot)$ is the activation function [20].

A neural network is constructed by neurons, containing three layers, namely, input, output, and hidden layer, which is shown in Figure 2.

The learning process of a neural network is to adjust the connection weight between neurons and the bias of neurons according to the training data [21]. The most commonly used algorithm for updating model parameters in neural networks is the error backpropagation (BP) algorithm, also known as the backpropagation algorithm [22]. Given the training data set $D = \{(x_1, y_1, y_2, y_2), \cdots (x_n, y_n)\}$, x_1, ER^d, y_1, the connection weight w_{ho} from the last hidden

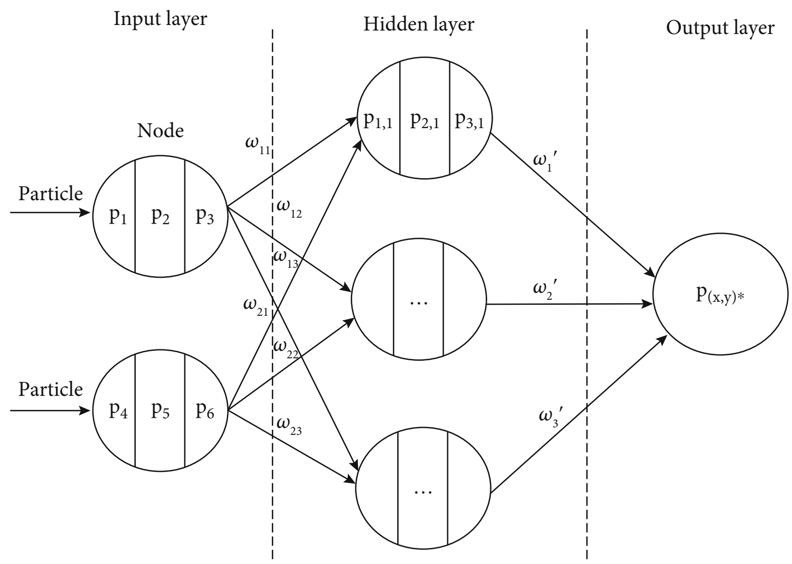

Figure 2: The neural network model.

layer to the output layer is used as an example to derive. For the training sample $y_k = (y_1^k, y_2^k \cdots, y_t^k)$, suppose the neural network output is

$$y_n^k = f\left(\sum_{9}^{n=1} w_{n0} c_n - \theta_n\right). \quad (2)$$

And the mean square error of the network in (x_k, y_k) is

$$E_k = \frac{1}{2} \sum_{l}^{n=1} \left(y_n^k - y_n^k\right)^2. \quad (3)$$

The parameter value is adjusted according to the negative gradient direction of the target [23]. For the error of Formula (3), given the learning rate μ, the connection weight w_{ho} is updated as follows:

$$\Delta w'_{ho} = -\mu \frac{\partial E_k}{\partial v_{loo}} = n\left(1 - y_0^k\right)\left(y_0^k - y_0^k\right) c_h. \quad (4)$$

Among them, $\partial E_k = \sum_q^{i=1} w_{ho} c_{ib}$, namely, the input of the *n-th* neuron in the output layer. The updated derivation of neuron bias θ is similar to it [24]. However, deep learning cannot directly use the BP algorithm for training and updating, since when the errors are propagated back in multiple hidden layers, they tend to diverge and cause instability to converge [25].

3. Network Fault Diagnosis Model Based on GAN

Figure 3 shows the dense heterogeneous wireless network scenario including high-power macro base stations and low-power micro base stations with a multilevel network structure. In addition [26], the heterogeneous network index parameters for macro base stations and low-power micro base stations are shown in Table 1.

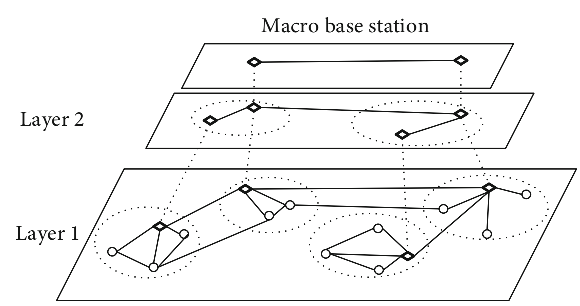

Figure 3: Two-layer heterogeneous wireless network model.

4. Fault Diagnosis Algorithm Based on Improved Generative Countermeasure Network

4.1. Semi-Supervised GAN Structure. Figure 4 shows the network structure.

Due to the change of the discriminator structure [27], the loss function of the semi-supervised generative adversarial network (SGAN) has also changed. The loss function of generator G is

$$L_G = E_{\hat{x} \sim p(\hat{x})}[\log P_d(y = K + 1 | \hat{x})]. \quad (5)$$

Among them, $\hat{x} = G(z)$ is the generator-generated data, and $P_d(y = K + 1 | \hat{x})$ represents the probability of which the generated data $\hat{x}$ is discriminated into the $K + 1$ category by the discriminator D [28].

The model structure is shown in Figure 5.

Increase the discriminator D, and take false data as the probability of true data, which can easily lead to the result that the generator G is overtrained on the current

Table 1: Corresponding indicators and standards for heterogeneous networks.

First-level index	Secondary indicators	Three-level indicators
Interference	Uplink interference	
	Downlink interference	
Coverage	Coverage boundary	
	Blind spots in coverage	
Hardware	Baseband control unit BBU	LMPT, LBBP
	Radio remote unit RRU	TRX, CPRI module, and synthesizer
	Antenna	
	RF transmission chain	PA, antenna feeder, and connector
	RF receiving chain	LNA, duplexer, and preselector
	Other hardware	Power supply and GPS clock module
Transmission	Interface	
	Link	
Other	Fading	
	Configuration parameter	

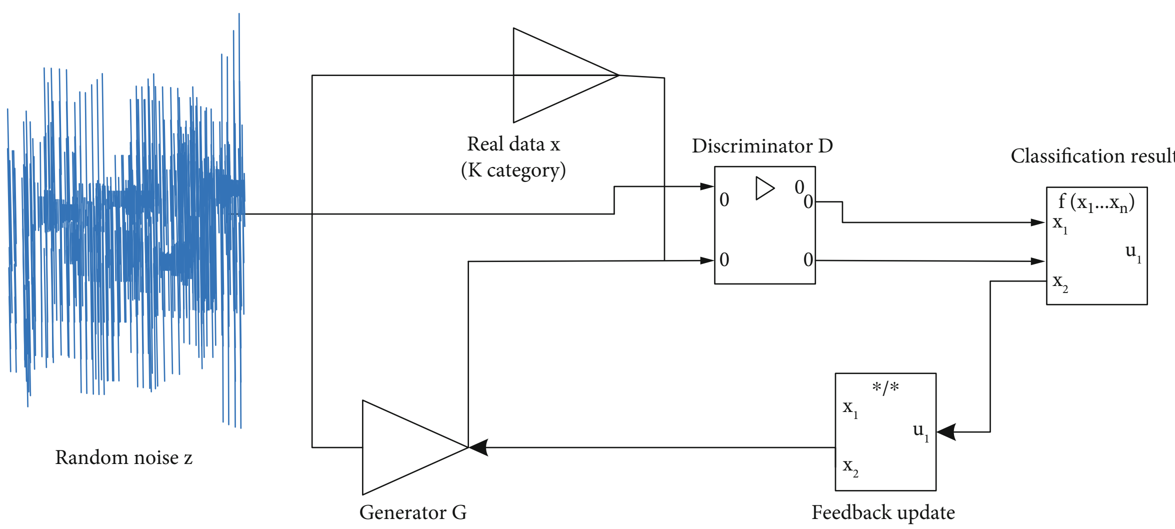

Figure 4: Semi-supervised generative adversarial network structure.

discriminator D, that is, when the parameters of the discriminators D change, the generator G will also be greatly affected. The algorithm flow of the improved SGAN is shown in Figure 6.

The specific parameters of the generated antagonistic neural network are shown in Table 2.

The data labels of 0 and 1 in the model are also smoothed to enhance the anti-interference ability of the network. And only the label of 1 is changed to 0.9, that is, the one-sided label is smoothed [29].

The process is shown in Figure 7.

4.2. Generating a Fault Diagnosis Model Combining a Confrontation Network and a Convolutional Neural Network. The fault diagnosis model of the combination of generative confrontation network and convolutional neural network proposed in this paper can be divided into fault diagnosis and data generation, which is shown in Figure 8.

(a) GAN generates network data

The data during this period time is summed and averaged to obtain the data at time t:

$$X^t = \begin{bmatrix} KPI_1^{t-T+1} & KPI_1^{t-T} & \cdots & KPI_1^t \\ KPI_2^{t-T+1} & KPI_2^{t-T} & \cdots & KPI_2^t \\ \vdots & \vdots & \ddots & \\ KPI_8^{t-T+1} & KPI_8^{t-T} & \cdots & KPI_8^t \end{bmatrix}$$

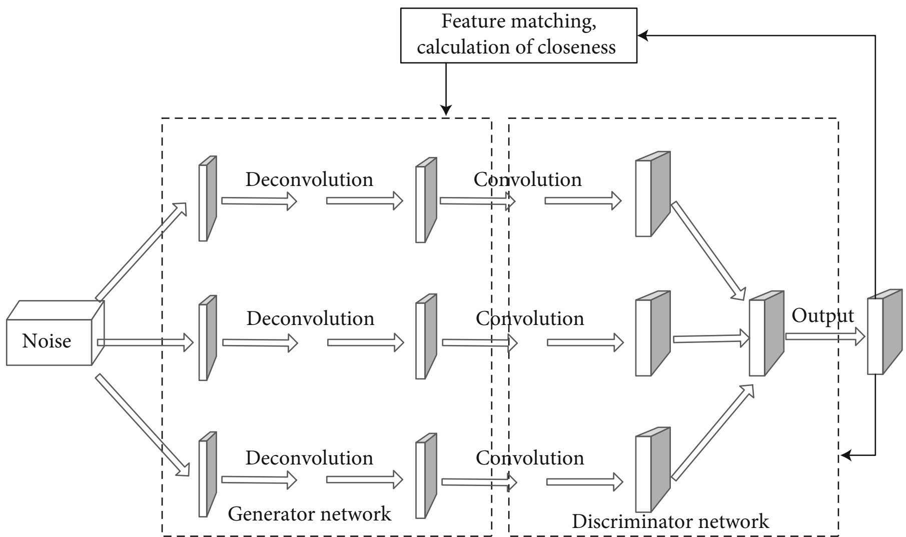

FIGURE 5: Fault diagnosis model based on the improved generative confrontation network.

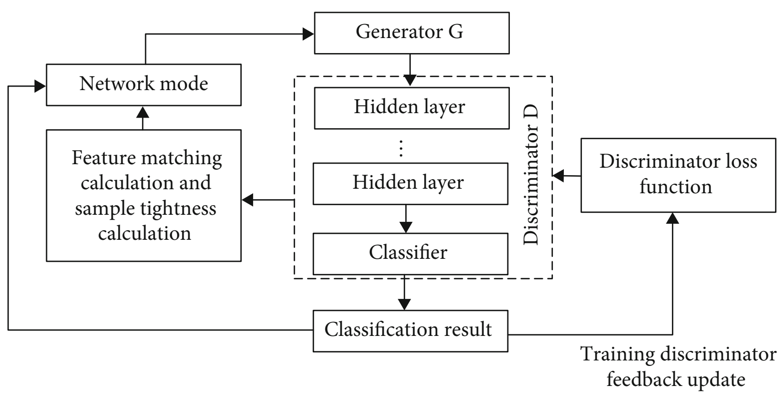

FIGURE 6: Algorithm flow chart of improved SGAN.

TABLE 2: Improved generative adversarial network model parameters.

Neural network name	Layer (operation)	Input format	Output format
Generator network	Fully connected layer	[None,128]	[None,256]
	Batch normalization (batch_norm)	[None,256]	[None,256]
	Nonlinear activation (ReLU)	[None,256]	[None,256]
	Deconvolution layer 1 (conv2d_transpose)	[None,2,2,64]	[None,4,4,16]
	Batch normalization (batch_norm)	[None,4,4,16]	[None,4,4,16]
	Nonlinear activation (ReLU)	[None,4,4,16]	[None,4,4,16]
	Deconvolution layer 2 (conv2d_transpose)	[None,4,4,16]	[None,8,8,1]
	Nonlinear activation (tanh)	[None,8,8,1]	[None,8,8,1]
Discriminator network	Convolutional layer 1 (conv2d)	[None,8,8,1]	[None,4,4,32]
	Batch normalization (batch_norm)	[None,4,4,32]	[None,4,4,32]
	Nonlinear activation (LeakyReLU)	[None,4,4,32]	[None,4,4,32]
	Convolutional layer 2 (conv2d)	[None,4,4,32]	[None,2,2,64]
	Batch normalization (batch_norm)	[None,2,2,64]	[None,2,2,64]
	Nonlinear activation (LeakyReLU)	[None,2,2,64]	[None,2,2,64]
	Fully connected layer	[None,256]	[None,7]
	Softmax	[None,7]	[None,7]

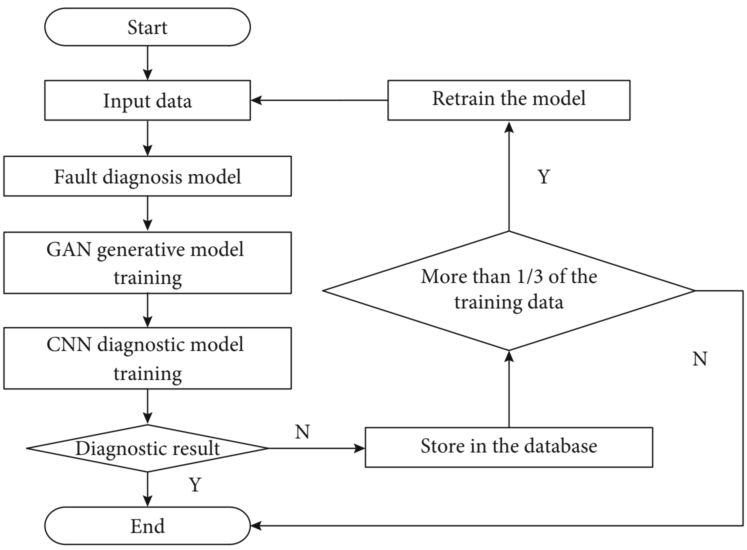

FIGURE 7: Model modification flow chart.

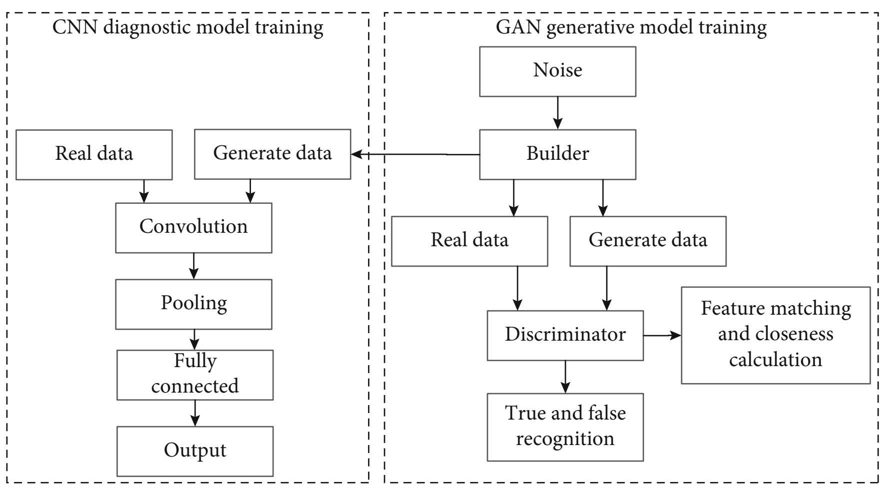

FIGURE 8: A fault diagnosis model combining generative adversarial network and convolutional neural network.

$$= \begin{bmatrix} \frac{1}{T}\Sigma_{i=t-T+1}^{t} KPI_1^i \\ \frac{1}{T}\Sigma_{i=t-T+1}^{t} KPI_2^i \\ \vdots \\ \frac{1}{T}\Sigma_{i=t-T+1}^{t} KPI_8^i \end{bmatrix} = \begin{bmatrix} KPI_{avg\_1}^t \\ KPI_{avg\_2}^t \\ \vdots \\ KPI_{avg\_8}^t \end{bmatrix} \quad (6)$$

Among them, KPI is used to refer to the abovementioned eight network key performance indicators.

(b) Network fault diagnosis model based on CNN

After completing the generation of various types of fault data, manually add corresponding fault labels for them, and then merge them with the real data as the training data set parameters of the convolutional neural network [30].

4.3. Construction of Fault Diagnosis Model Based on Improved SGAN. The constructed heterogeneous wireless network system collects the data and manually adds tags to the data according to the preset failure time. The improved SGAN diagnosis model diagnosis process is shown in Figure 9.

(1) Data preprocessing

For the NULL value data x_i in the collected data, fill in according to Formula 16, where x_{i-1}, x_{i+1} are the previous sample value and the next sample value of x_i :

$$x_i = \frac{x_{i-1} + x_{i-1}}{2} \quad (7)$$

For the optimal feature selection, an algorithm that combines ReliefF and mutual information is used to select the optimal feature subset.

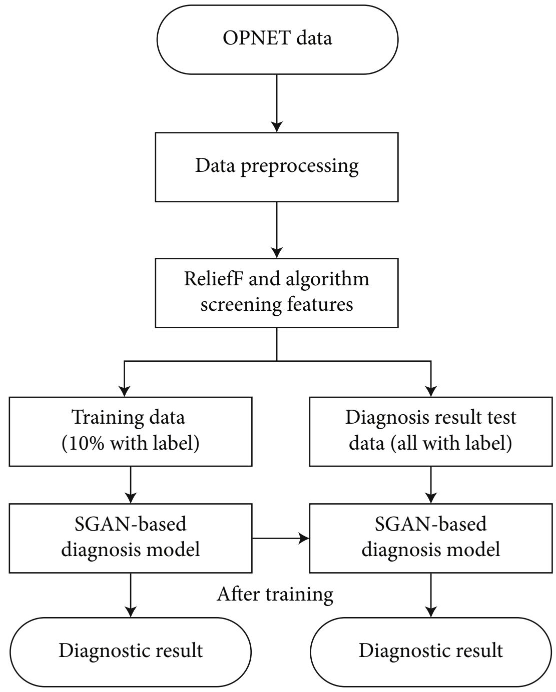

Figure 9: Diagnosis process based on improved SGAN model.

Table 3: Two-layer heterogeneous wireless network simulation parameters.

Simulation parameters	Macro base station	Micro base station
Number of base stations	3	15
Number of users	20/base station	10/base station
Transmission power	46 dBm	30 dBm
Shadow fading standard deviation	8 dB	10 dB
Transmission loss model	Suburban macrocell (3GPP)/free space	Indoor office environment (ITU-R M. 1225)/outdoor to indoor and pedestrian environment
Antenna gain	15dBi	8 dBi
Operating mode	LTE 5 MHz FDD	LTE 10 MHz FDD
Receiving sensitivity	-110 dBm	-107 dBm
Base station selection strategy	Best suitable eNodeB	
User distribution	Random distribution	

(2) Improved SGAN fault diagnosis model

To build the SGAN model in Pycharm based on the Python language and TensorFlow framework, the three modules of TensorFlow, numpy, and time are first imported. The TensorFlow module mainly completes the neural network construction and provides functions such as reverse update, the numpy module mainly provides functions such as calculation and format conversion between data matrices, and the time module mainly provides the timing function. Then read the data, and perform one-hot encoding on the label to build a generator network. The parameter format of the discriminator network is as follows. The size of the convolution kernel is 3×3, and *dis_vars* is the connection weight and bias number in the discriminator network.

5. Experimental Test

A heterogeneous wireless network scenario is built through simulation software to set up various faults and run the system to collect data. Moreover, the collected data is cleaned and feature engineering process, and the preprocessed data is input into the training model. After the model is trained, the network operation data will be input to the model for fault diagnosis.

5.1. Experiment Platform. The parameters are shown in Table 3.

In the network simulation, this paper mainly sets five different types of faults, namely, uplink interference F_1, downlink interference F_2, coverage failure F_3, base station

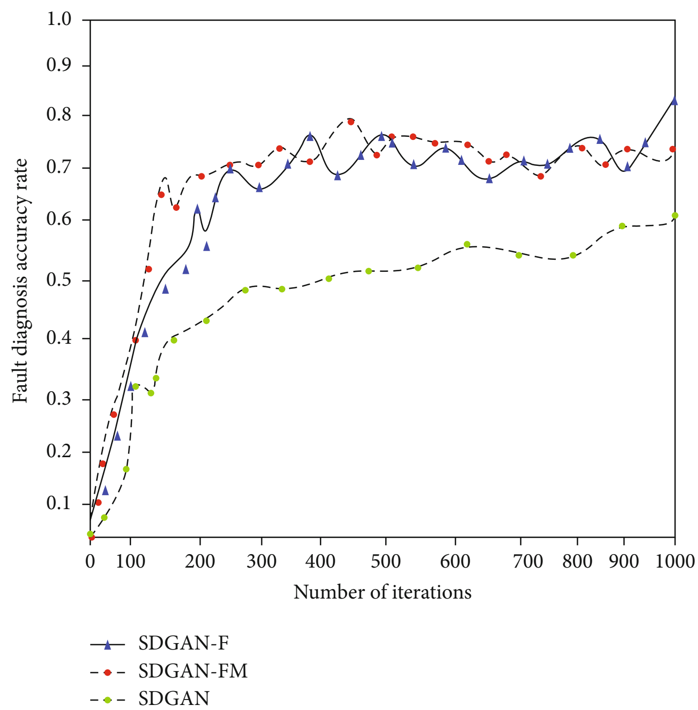

Figure 10: Changes in the accuracy of fault diagnosis based on different improved methods.

failure F_4 and link failure F_5, and fault-free state F_0. Before the simulation starts, the occurrence and recovery time of these faults will be set in advance to manually add fault labels to the data generated by the simulation. The time set for the simulation is 24 hours, and the total duration of each fault is 2 hours [31]. Each fault lasts for 30 minutes and then recovers. Finally, 29160 pieces of data are generated in the network simulation, and 1620 pieces of data are obtained after normalization and neighbor base station preprocessing, which are divided into training data and test data in a proportion of 7 : 3, and the proportion of various types of faults in each data set is ensured to be consistent. Then, the fault labels of about 1/10 of the training data are retained, and the fault labels of the rest of the training data are deleted. Finally, three data sets are formed, namely, 120 training data sets with fault labels, 1014 training data sets without fault labels, and 486 test data sets. The proportion of various types of faults in each data set is consistent. Finally, these data are input into the improved generative antagonistic network diagnosis model proposed in this paper for training and testing.

5.2. Analysis of Experimental Results. The change of the fault diagnosis accuracy rate of the generative confrontation network model based on different improved methods is shown in Figure 10.

Compared with SDGAN, due to the addition of the feature matching constraint function, SDGAN-F stabilizes the convergence fluctuation in the training process. However, the accuracy of its fault diagnosis still needs to be improved compared with the SDGAN-FM proposed in this paper. In addition, the accuracy rate of final fault diagnosis of SDGAN-FM algorithm can reach 92.2% comparing with 69% of SDGAN-F.

6. Conclusion

Compared with some traditional fault diagnosis methods, the algorithm proposed in this paper simplifies the difficulty of mapping between network symptoms and network faults. Moreover, through the deep neural network, the useful information in the data is fully excavated, and the diagnosis accuracy and diagnosis delay are improved. However, there are still some problems that need to be improved and solved. When the network structure changes, the diagnostic accuracy of the previously trained model may be affected. Therefore, the generalization ability of the model needs to be strengthened.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contributions

The authors of the manuscript "Optimized Fault Diagnosis Algorithm under GAN and CNN Hybrid Model" declare the following contributions to the creation of the manuscript: Xiaobo Zhu contributed to the conceptualization, resources, and methodology, while Yunlong Ye contributed to the supervision, project administration, and writing.

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